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Do Stock Markets Discipline US Bank Holding Companies: Just Monitoring, or also Influencing?

Abstract

This paper presents evidence that bank managers adjust key strategic variables following a risk and/or valuation signal from the stock market. Banks receive a risk signal when they exhibit substantially higher (semi-)volatility compared to the best performing bank(s) with similar characteristics, and a valuation signal when they are undervalued relative to the average bank with similar characteristics. We document, using a partial adjustment model, that bank managers adjust the long-term target value of key strategic variables and the speed of adjustment towards those targets following a risk and/or negative valuation signal. We interpret this as evidence of stock market influencing. We show that our results are unlikely to be driven by indirect influencing by regulators, subordinated debtholders, retail or wholesale depositors. Finally, we show that the likelihood that banks receive a risk and/or valuation signal increases with opaqueness, managerial discretion and specialization.

Keywords: market discipline; influencing; partial adjustment; opaqueness; bank risk

JEL: G21, G28, L25

1 Introduction

It is generally assumed that bank managers are disciplined by internal governance mechanisms and by their supervisors. Whether or not banks are also disciplined by financial markets is less clear. Yet, the Basel capital adequacy rules, one of the cornerstones of modern bank regulation, mention market discipline as a separate third pillar (next to capital ratios and supervisory interventions). Relatedly, stress testing exercises have expanded the disclosure requirements of banks, with the explicit objective to foster market discipline. In this paper we revisit this issue by focusing on the stock market as a potential source of market discipline on banks. The crucial question is: Can the stock market assess bank risk *and* influence bank behavior?

Bliss and Flannery (2002) distinguish two components of market discipline: market monitoring and market influencing. They define market monitoring as the ability of securityholders to accurately assess the condition of the firm, and influencing as subsequent managerial actions in response to these assessments. While there is considerable evidence of market monitoring (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990) and Morgan and Stiroh (2001)), research examining the market influencing channel is more scarce and generally inconclusive. Bliss and Flannery (2002) fail to find evidence that bank stockholders or bondholders effectively influence bank indicators controlled by bank managers, such as the leverage position of the BHC, factors affecting bank asset risk, changes in the number of employees and the amount of uninsured liabilities. Gendreau and Humphrey (1980) find that banks are penalized for higher leverage by a higher cost of debt and equity, but find no evidence that these relative cost changes induce bank managers to alter their leverage position relative to other banks. Ashcraft (2008) shows that the proportion of subordinated debt in total regulatory capital affects the probability of failure and future distress, suggesting that bank debtholders are able to significantly influence the behavior of distressed banks. Schaeck, Cihak, Maechler, and Stolz (2012) find evidence for debtholder discipline in a sample of small and medium-sized commercial banks in the US over the period 1990-2007: Bank managers are more likely to be removed if the bank is financially weak and this effect is stronger for banks subject to discipline exerted by large debtholders. The authors find no conclusive evidence of discipline exerted by shareholders or depositors, nor that forced turnovers consistently improve bank performance (even at windows of three years after the turnover). Hence, current empirical research predominantly supports the view that market discipline is, at best, a relatively weak disciplining device.

The main contribution of this paper is the design of a new test for direct market influencing. Our procedure starts by identifying stock market-based risk and (negative) valuation signals at the individual bank level. Consequently, we test to what extent bank managers adjust key strategic variables following a (combination of a) risk and negative valuation signal. Using a partial adjustment model, we test both for a change in the long-term target value of the strategic variable, as well as in the speed of adjustment towards that long-term target value. This partial adjustment model has been used quite often to model various firm characteristics, for example by Flannery and Rangan (2006) and Flannery and Rangan (2008) for leverage, Lintner (1956) for dividend payout ratios and Fama and French (2000), Raymar (1991) and Sarkar and Zapatero (2003) for earnings.

An important innovation is the way we define the risk and valuation signals. We model our risk measure, equity return semi-volatility (SV, henceforth), measured over one quarter of daily data, along a stochastic frontier. The stochastic frontier describes the level of risk that the best performing banks with similar characteristics can attain. We call a bank inefficient from a risk perspective when it is situated above the risk frontier, i.e. when it has more risk than its best performing peers. A bank will receive a risk signal at time t if its inefficiency score at that time is situated among the 10 percent worst inefficiency scores of all banks over the preceding four years and is hence substantially above the risk frontier. We use a similar approach for our valuation measure, the market-to-book (MTB) ratio, only here we allow banks to be either under- or overvalued relative to the average bank with similar characteristics. We say that a bank receives a negative valuation signal when its quarterly valuation score belongs to the 10 percent largest undervaluations (of all banks, over the preceding four years). Looking at large signals relative to the best performing peer is crucial. As market prices are forward looking, they reflect information on firms' fundamentals, but also on expected corrective actions. If investors expect a corrective action, the resulting signal will be smaller (Bond, Goldstein, and Prescott (2010)). Using the most extreme signals makes it less likely that we look at events where investors have strong expectations on corrective behavior. Nevertheless, the results are robust (but unreported) when using the 25 percent worst inefficiency or valuation scores as signals.

The main result of this paper is that we find substantial evidence in favor of the direct market influencing hypothesis. We show that banks that receive a risk signal react by increasing their long-term target capital buffer and by decreasing their liquidity risk. Banks that receive a negative valuation signal react by increasing their target profit level, primarily by lowering the cost-to-income ratio. This suggests that managers trying to improve the market assessment of their bank's value attempt this mainly by improving cost efficiency. Apart from adjusting their long-term target ratios, we also find banks to more quickly bridge the gap between the current and target rate following a market signal. These adjustments are in line with expectations and with the objectives of supervisors.

Furthermore, we investigate whether or not our findings can be interpreted as evidence of direct influencing rather than indirect influencing. Indirect market discipline means that the change in bank behavior is enforced by other stakeholders (e.g. supervisors) than the stakeholder (shareholders in our case) exerting the monitoring effort. First, we argue that the number of Prompt Corrective Actions (PCAs) is so small that our signals are unlikely to be proxies for regulatory interventions. Second, our results do not appear to be driven by influencing from subordinated debtholders, as we find that our influencing results are most pronounced for those banks that do not have subordinated debt. Third, we test whether or not our results are potentially driven by influencing exercised by retail or wholesale deposit holders. We do observe that the share of retail funding in total funding is larger for banks receiving a risk signal. This is mainly due to increasing the core deposits, and we do not find evidence that it is more likely for a bank to lose wholesale funding following a risk signal. Nevertheless, as in most other studies addressing this issue, there is still a need for caution since other sources of discipline, such as unobserved actions taken by the supervisory authorities, may affect bank behavior. Finally, we investigate in more detail which characteristics make it more likely that a bank will receive a risk or valuation signal. We consider the variance of the signal to be the scope for pressure from stock market investors. Therefore, in an extension of our setup, we allow the variance of the residuals to vary through time and change with bank characteristics. We find that stock market investors punish discretionary accounting behavior and that the degree of bank opacity has a positive effect on the variance of the residuals (and hence the likelihood of observing market signals).

The remainder of this paper is structured as follows. Section 2 introduces a new setup to assess the different components of market discipline, i.e. market monitoring and influencing, in a unified framework. The first part discusses the stochastic frontier model for Semi-Volatility and the linear regression model for the Market-to-Book ratio. Next, we show how to extract risk and valuation signals from both models. The final section presents the partial adjustment model that we use to empirically test for market influencing. Section 3 contains the main empirical findings for the influencing hypothesis. In Section 4, we show that the results are evidence of direct influencing following stock market signals, rather than indirect influencing via regulators or wholesale financiers. In Section 5 we analyze which banks are more likely to get signals. A final section concludes.

2 A New Setup to Test Market Discipline

2.1 Monitoring by Equityholders

Bliss and Flannery (2002) define market monitoring as the ability of securityholders to accurately assess the condition of the firm. Previous papers have tested the market monitoring hypothesis by relating bank risk and valuation to bank-specific characteristics in a linear regression framework (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990), Stiroh (2004), Stiroh (2006b), Hirtle and Stiroh (2007), Calomiris and Nissim (2007)):

$$Y_{i,t} = \beta_0 + \beta X_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

Equation (1) relates bank-specific stock market-based risk and valuation measures $Y_{i,t}$ to various lagged[1] bank-specific characteristics $X_{i,t}$. We relate the dependent variable to four sets of bank characteristics, proxying for respectively: (i) the bank's funding structure, (ii) asset mix, (iii) revenue diversity and (iv) overall bank strategy. Our vector $X_{i,t}$ of bank-specific characteristics, which appears in Equation (1), is hence given by:

$$X_{i,t} = [Bank\ Strategy,\ Funding\ Structure,\ Asset\ Mix,\ Revenue\ Streams]_{i,t} \tag{2}$$

Following Calomiris and Nissim (2007), we use the market-to-book value of equity as a measure of the long-run value of the bank. The market-to-book value of equity (MTB) is measured as the end of quarter market value divided by tangible common equity. As a measure of risk, we use the quarterly semi-volatility (SV)[2] measured over a quarterly moving window of excess stock returns for bank i (excess over the risk-free return). Instead of using a linear regression for risk, we model semi-volatility along a stochastic frontier.[3] This allows us distinguishing between banks that are on the frontier (given the characteristics associated with their business model) and risk inefficient banks. The best performing bank, relative to its peers with

[1] We use one-quarter lagged values rather than contemporaneous values to account for the lag with which accounting information is disclosed. A detailed appendix discusses the construction of these indicators with a reference to the FRY9C codes of the constitutent items.

[2] Semi-volatility or semi-deviation potentially captures downside risk better than total volatility. The latter is calculated using both upside and downside changes in returns, whereas the former uses only downside returns (below the average). However, the correlation between the two measures is high. The results presented in the paper also hold when using total volatility. Results are available upon request.

[3] Stochastic frontier analysis is also a parametric approach. A non-parametric equivalent is data envelopment analysis as used for instance by Lee and Chih (2013).

similar characteristics, has minimal risk, and will be situated close or on the frontier.[4] We call banks risk inefficient if they are situated (much) above the frontier, i.e. have much more risk compared to their best performing peers.

Summary statistics on the dependent and independent variables are reported in Table 1. Our sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters in the period 1991-2007.[5] The total sample consists of $17,264$ observations on 899 bank holding companies. We exclude illiquid stocks as well as control for important mergers and acquisitions[6].

< Insert Table 1 around here >

Finding significant relationships between these bank characteristics and the risk and valuation measure would be evidence of the first step in market discipline, market monitoring. If so, we can conclude that equityholders track the different risks associated with the balance sheet and income statement characteristics. Many studies already addressed the issue of bank monitoring, i.e. the first step in a test for market discipline, by relating bank risk and/or return to bank-specific characteristics (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990), Stiroh (2004), Stiroh (2006b), Hirtle and Stiroh (2007) or (Calomiris and Nissim (2007)). Our focus and contribution lies in testing for market influencing. Nevertheless, to allow comparison with existing studies and to be transparent with respect to the other steps of the analysis, we briefly describe the results of the baseline equation of monitoring in an appendix. While not the main contribution of this paper, we believe we still add to this literature by considering a more comprehensive range of bank characteristics.

[4] More specifically, contrary to the linear model, we assume that the part of $SV_{i,t}$ not explained by bank characteristics can be further decomposed in a pure noise component, $\nu_{i,t} \sim iid\ N(0, \sigma_v^2)$ and in one-sided departures (risk inefficiencies), $u_{i,t}$, from the stochastic frontier. The stochastic frontier is determined by the equation $\hat{\beta}_0 + \hat{\beta} X_{i,t-1}$.

[5] All data are collected from the publicly available FR Y-9C reports. Consequently, we link the FR Y-9C reports to banks' stock prices (obtained from CRSP) using the match provided on the Federal Reserve Bank of New York website http://www.ny.frb.org/research/banking_research/datasets.html

[6] As a liquidity threshold, we impose that the bank stock's traded volume should be non-zero in at least 80 percent of trading days during the quarter. We control for mergers and acquisitions and create a new bank identity whenever a bank's total assets increase more than 10% on a quarterly basis and there is a change in activity mix. The change in activity mix is identified as follows. We measure activities along three dimensions (funding structure, loan portfolio composition and revenue mix). For each of these dimensions, we create a measure of focus/diversification. If there is a large change in focus in one of these measures, i.e. a change larger than one standard deviation, within three years after a large jump in total assets (10% growth on a quarterly basis), we label this as a change in activity composition following the expansion.

2.2 Extracting Stock Market Signals

Market influencing refers to managerial actions in response to the risk and valuation assessments made in the market monitoring stage (Bliss and Flannery (2002)). Hence, for the purpose of our study, the crucial output from this first stage regression described in the previous section are risk and valuation signals. We say a bank receives an undervaluation signal when its residual (calculated using equation (1)) belongs to the bottom decile. Equityholders are said to give a risk signal if the inefficiency score is situated in the highest decile, where risk inefficiency is measured as the difference between the bank's semi-volatility and the stochastic frontier (representing similar banks with the lowest risk). By only looking at the most extreme deciles, we reduce the likelihood that investors incorporate the expected response in their assessment. Put differently, if investors expect a corrective action (as in Bond, Goldstein, and Prescott (2010)), the resulting residual/inefficiency score will be smaller. This actually works against establishing a link between signals and outcome variables, as we only exploit the information in signals where stock market investors have low expectations of subsequent corrective behavior. We form deciles over a backward-looking, moving window of four years, as the intensity of market discipline may vary over time.[7]

The upper panel of Figure 1 provides information on the level and dynamics of the risk inefficiency scores (left hand side) and MTB residuals (right hand side), whereas the lower panel B provides information on the frequency of banks getting a signal. Each subplot of the upper panel A presents the average inefficiency score (the deviation from the stochastic frontier or the fitted regression line) of three portfolios in "event time". Each quarter, we sort BHCs into deciles according to the level of the market signal[8]. The most extreme decile (highest risk or lowest value) is represented by the thick line. We also report the least extreme decile as well as the two middle deciles (combined in one line). The portfolio formation quarter is denoted as time period 1. We then compute the average inefficiency score for each portfolio in each of the subsequent 10 quarters,

[7] We thus estimate the monitoring (or 'rules') equation using the full sample period, but determine the signals in a backward looking way. Hence, we assume that the bank knows the benchmark equation used by investors to benchmark value or risk, but that future realizations are unknown when determining current signals. Rather than using the entire history of data (which would imply more information for later periods), we employ a backward looking rolling window. The latter approach is motivated by the 'institutional memory hypothesis' that implies that only a recent horizon matters and not the full history (see e.g. Berger and Udell (2004)). We set the length of the moving window at 4 years (we did experiment with windows of 5 and 6 years and get similar results).

[8] The figure is inspired by Lemmon, Roberts, and Zender (2008), who investigate the persistence of firm capital ratios. This methodology is ideally suited for investigating the cross-sectional dispersion and time evolution of bank characteristics over longer periods.

holding the portfolio composition constant (except for BHCs that exit the sample). We repeat these two steps of sorting and averaging for every quarter in the sample period (1993-2007). This process generates 60 sets of event-time averages, one for each quarter in our sample. We then compute the average risk inefficiency score and undervaluation residual of each portfolio across the 60 sets within each event quarter. The dashed lines surrounding the portfolio averages represent 90% confidence intervals. They are computed as the average standard error across the 60 sets of averages (Lemmon, Roberts, and Zender (2008)).

< Insert Figure 1 around here >

At portfolio formation time (event time 1), there are large and significant differences between the three groups. The differences between the extreme signal and the average signal remain significant for about 5 to 6 quarters. The risk inefficiency score of the highest decile portfolio improves substantially in the first four quarters after which portfolios are created, but is still significantly higher than the mean. The persistence in the market-to-book signal is even slightly higher than the stickiness of the SV signal. Differences between the best and worst group are even more persistent. The graphs show that there is substantial between and within variation in the signals, which will allow us to identify whether or not banks respond to temporary signals. The graph also highlights that extreme market signals are sticky in the medium run but are not persistent or long-lived.

The lower panel B of Figure 1 provides information on the fraction of banks that receive a risk or valuation signal in a given quarter. The unconditional benchmark is 10% as we look at the extreme decile of signals. A number in excess of 0.1 at time t indicates that there are more banks underperforming at time t relative to the previous four years. We observe an increase in the likelihood of reveicing a negative valuation signal in the late nineties and in 2006. The peaks in risk signals we identify coincide with the 1998 banking crisis (induced by the Russian collapse and the LTCM debacle) and the early millennium recession, as well as the onset of the global financial crisis in 2007.[9]

2.3 Influencing by Equityholders

The influencing channel of market discipline implies that bankers should take off-setting actions to align their performance with the interest of monitors, which are stock market investors in the context of this paper. We investigate the market influencing hypothesis by testing whether or not bank managers make strategic

[9] The time series of the frequency of banks receiving a signal is similar when using total volatility or the full sample period (rather than using a backward looking, 4 year moving window horizon).

reallocations following a negative risk and/or valuation signal. We are particularly interested in the effect of market signals on the capital ratio and the profitability of the bank (here measured as ROE), since an increase in bank capital reduces risk and higher profits boost bank value. However, strategic reallocations may take different forms. Therefore, we focus on an set of seven strategic bank characteristic which are next to the capital ratio and profitability (ROE), also asset quality (non-performing loans ratio), cost inefficiency (cost-to-income ratio), liquidity (the ratio of liquid assets to total assets), the ratio of non-interest income to total income and the dividend pay-out ratio. The five additional strategic bank variables can be interpreted as the underlying drivers of profits and capital levels. We believe that these ratios reflect the main strategic decision variables directly under the control of bank management.

To account for a gradual and potentially incomplete adjustment in the different strategic variables, we estimate a partial adjustment model.[10] The general specification for a partial adjustment model is:

$$\Delta y_{i,t} = \gamma(y^* - y_{i,t-\tau}) + \varepsilon_{i,t} \tag{3}$$

where y represents a strategic bank characteristic, y^* is the target level of y and γ the speed of convergence to this target level. To formally test for market influencing, we investigate whether or not (i) the implied target level is different for banks that receive a market signal and (ii) banks receiving a market signal converge faster to the target. Therefore, Equation (3) is modified such that the adjustment speed and target level can vary by bank and over time:

$$\Delta y_{i,t} = \left(\gamma_0 + \gamma_0^* D^y_{i,t-\tau} + \gamma_1 D^{SV}_{i,t-\tau} + \gamma_2 D^{MTB}_{i,t-\tau} + \gamma_3 D^{SV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}\right) \times \left(y^*_{i,t} - y_{i,t-\tau}\right) + \varepsilon_{i,t}$$

with

$$y^*_{i,t} = f(D^y_{i,t-\tau},\ D^{SV}_{i,t-\tau},\ D^{MTB}_{i,t-\tau},\ X_{i,t-\tau}) \tag{4}$$

where $D^{SV}_{i,t-\tau}$ is a dummy variable equal to one if bank i receives a risk signal at time period $t-\tau$. Similarly, $D^{MTB}_{i,t-\tau}$ is a dummy variable equal to one if bank i receives a valuation signal at time period $t-\tau$. The interaction term $(D^{SV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau})$ captures the additional effect of banks receiving both signals simultaneously. Since bank strategies are sticky in the short term and restructuring typically occurs as a series of incremental adjustments, we measure reallocations over a two year period and define $\tau = 8$ quarters to estimate Equation

[10] The partial adjustment model has been used quite often to model various firm characteristics, for example by Flannery and Rangan (2006) for firm leverage (Flannery and Rangan (2008) for bank leverage), Lintner (1956) for dividend payout ratios and Fama and French (2000), Raymar (1991) and Sarkar and Zapatero (2003) for earnings.

(4).[11] In addition, we allow for a different target level and a different speed of adjustment for banks that are situated in the worst decile of the cross-sectional distribution of the strategic bank characteristic ($D^y_{i,t-\tau}$ is a dummy variable equal to one if the strategic bank characteristic for bank i at time $t-\tau$ is weak and zero otherwise). Finally, we allow the target level y^* to be a function of the other strategic bank characteristics $X_{i,t-\tau}$ (i.e. the eight strategic bank characteristics excluding the dependent variable). We estimate a reduced form of Equation (4), for each of the seven strategic bank variables:

$$\Delta y_{i,t} = \begin{array}{c} c_0 + c_1 D^y_{i,t-\tau} + c_2 D^{SV}_{i,t-\tau} + c_3 D^{MTB}_{i,t-\tau} + c_4 D^{SV}_{i,t-\tau} D^{MTB}_{i,t-\tau} + X_{i,t-\tau}\beta \\ + c_5 y_{i,t-\tau} + c_6 D^y_{i,t-\tau} y_{i,t-\tau} + c_7 D^{SV}_{i,t-\tau} y_{i,t-\tau} + c_8 D^{MTB}_{i,t-\tau} y_{i,t-\tau} + c_9 D^{SV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau} y_{i,t-\tau} + \varepsilon_{i,t} \end{array} \tag{5}$$

Pooling all terms that contain $y_{i,t-\tau}$ (and bringing this combination in front) yields:

$$\Delta y_{i,t} = \begin{array}{c} -\left(c_5 + c_6 D^y_{i,t-\tau} + c_7 D^{SV}_{i,t-\tau} + c_8 D^{MTB}_{i,t-\tau} + c_9 D^{SV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}\right) \\ \times \left[\frac{c_0 + c_1 D^y_{i,t-\tau} + c_2 D^{SV}_{i,t-\tau} + c_3 D^{MTB}_{i,t-\tau} + c_4 D^{SV}_{i,t-\tau} D^{MTB}_{i,t-\tau} + X_{i,t-\tau}\beta}{-\left(c_5 + c_6 D^y_{i,t-\tau} + c_7 D^{SV}_{i,t-\tau} + c_8 D^{MTB}_{i,t-\tau} + c_9 D^{SV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}\right)} - y_{i,t-\tau} \right] + \varepsilon_{i,t} \end{array} \tag{6}$$

Hence, the term before the square brackets corresponds with the first term in Equation (4), whereas the first term in square brackets corresponds with the expression of the conditional target, y^*in Equation (4). Rather than reporting the estimated coefficients of the reduced-form partial adjustment model[12], which we estimate for each of the seven strategic bank variables under consideration, we summarize the relevant information in two statistics that we think are easy to interpret: the long-run target level and adjustment speed. Calculating the target levels and speed of adjustment for the eight indicators using the coefficients of Equation (6) results in eight 2 by 2 matrices in Table 2:

	$D^{MTB}_{i,t-\tau} = 0$	$D^{MTB}_{i,t-\tau} = 1$
$D^{SV}_{i,t-\tau} = 0$	$-\frac{c_0}{c_5}$	$-\frac{c_0+c_3}{c_5+c_8}$
$D^{SV}_{i,t-\tau} = 1$	$-\frac{c_0+c_2}{c_5+c_7}$	$-\frac{c_0+c_2+c_3+c_4}{c_5+c_7+c_8+c_9}$

and

	$D^{MTB}_{i,t-\tau} = 0$	$D^{MTB}_{i,t-\tau} = 1$
$D^{SV}_{i,t-\tau} = 0$	$-c_5$	$-(c_5 + c_8)$
$D^{SV}_{i,t-\tau} = 1$	$-(c_5 + c_7)$	$-(c_5 + c_7 + c_8 + c_9)$

The left[13] hand side table contains information on the target level of the bank characteristic. The upper

[11] A concern is that the worst performers, which are more likely to fail or be acquired, would bias the results. Therefore, we discard all observations up to eight quarters before the last quarter the BHC appears in the sample. Hence, this implies that the last potential signal for each BHC occurs 16 quarters before the BHC disappears from the sample (as we look at a change in strategic bank variables over a period of eight quarters following a risk or valuation signal).

[12] Results are available upon request.

[13] We evaluate the expression of the targets at the sample mean of the variables in the X-vector. As we standardize all variables in the X-vector , this simply implies that they drop from the equation. Furthermore, in the paper we report results when the dummy variable $D^y_{i,t-\tau} = 1$. Results for $D^y_{i,t-\tau} = 0$ are similar and available upon request.

left cell is the target level for each of the strategy variables implied by the influencing equation in the absence of market signals. The upper right cell contains the target level when there is only a valuation signal and the lower left cell shows the target level in case of only a risk signal. The lower right cell contains the target level when both market signals occur simultaneously. In each case we report the p-value to assess the statistical significance[14] of the differences with the benchmark case of no signals, i.e. the upper left cell. In the right hand side panel, the corresponding findings for the speed of adjustment are presented. Hence, from this table we can infer whether or not the target level and speed of adjustment are different for banks receiving either a risk signal, a valuation signal or both.

3 A New Test of Market Influencing: Empirical Results

Table 2 contains the main results of this paper and are generally supportive for the hypothesis of stock market influencing in US banking. Starting with the capital ratio and bank profitability (here measured as ROE), we expect to find that bank capital increases after a risk signal and that a negative valuation signal induces bank management to improve profitability. The target capital ratio in the no-signal case is 11.5%, which is in line with the summary statistics reported in Table 1. Banks that receive a risk signal (SV inefficiency in the highest decile) have a significantly higher target capital ratio (12.2%). This indicates that bank management reacts to a perceived increase in the riskiness of their bank by increasing the capital buffer, as expected. Banks that receive a valuation signal from the stock market react by adjusting the target capital ratio downwards (to 10.4%) and at a much faster speed. This is in line with the results of Table A.1 (in appendix) which indicate that higher capitalized banks have lower risk and lower market-to-book ratios. These findings support the hypothesis that banks adjust their capital adequacy target as a reaction to pressure from the stock market. On the profit side, we observe that the target ROE ratio slightly decreases from 3.4% to 3.2% when the bank receives a risk signal from the stock market. However, in case the bank gets a valuation signal, bank management reacts by significantly increasing the target profit level (to 4.1%). Note that ROE is expressed at the quarterly frequency. On an annual basis, this implies an increase in target ROE from 13.6% to 16.4%. Hence, bank management responds to market pressure by signaling a strategic refocusing aimed at increasing ROE, although the speed of adjustment does not change significantly, presumably indicating that increased profits take time to materialize.

[14] We cluster the standard errors at the bank level in the estimation of Equation (4).

< Insert Table 2 around here >

The other strategic bank variables can be interpreted as the underlying drivers of profits and capital levels. The following picture emerges. When banks are confronted with a risk signal, they not only adjust their target capital level upwards, but also reduce their liquidity risk by increasing the target liquid assets ratio from 2.6% to 4.8%. The target level for the reliance on non-interest income is lowered substantially, although slightly insignificant at the 10% level, but the speed of adjustment towards the target increases from 15% to 28%. Banks in the highest risk inefficiency decile tend to increase their target proportion of non-performing loans, which may be surprising at first. However, credit risk in the loan portfolio is only one dimension of total bank risk, which we measure as semi-volatility. The increased non-performing loans ratio may be the outcome of increased transparency (i.e. management having to report more accurately), rather than an actual change in credit risk.

We showed before that in case of a valuation signal, banks respond by increasing their target ROE level. Table 2 shows that at the same time, bank managers substantially and significantly reduce the target cost-to-income ratio (from 61.4% in the base case to 55.0%). This indicates that bank managers try to improve profits primarily by focusing on the cost efficiency of their organization. Since management has a large degree of discretion in altering the bank's cost structure[15], this may be interpreted as a credible signal by the stock market. When both signals occur simultaneously, the most pronounced impact, both economically and statistically, can be observed for the implied target levels of the retail funding ratio (from 65.5% to 81.5%).

The findings for the speed of adjustment towards the implied target levels exhibit a similar pattern, although the degree of significance is usually lower. Nevertheless, whenever the adjustment speed is statistically different from the benchmark no-signal case, the evidence points in the direction of a faster adjustment towards the target. Hence, banks respond by either changing a strategic bank characteristics or by reacting

[15] In unreported regressions, we investigate whether decisions in human capital management take place in response to market signals. As a dependent variable, we constructed a binary variable, equal to one if a drop in full-time equivalent employees takes place over a two year horizon, and equal to 0 in all other cases. The effect of market signals is investigated with a probit regression. The control variables in this set-up are the eight quarter lag in the number of employees, in addition to the strategic bank characteristics that are also included in the specification of the target (Equation (4)). To investigate the potential reaction to market signals, both the risk signal, the valuation signal and the interaction of both are included. The constant in the probit regression indicates that the average probability for a layoff is 22%. The most important determinant of the probability of lay-offs, both in economic and statistical terms, is past profitability. In addition, the likelihood of layoffs is 11% higher for banks that simultaneously get a risk and valuation signal.

more swiftly to deviations from the optimal level. Based on these results, we conclude that bank management does react to stock market-based risk and valuation signals. Market signals influence banks to adjust the target levels of capital, profits and the main drivers of these two strategic indicators in the requested direction. Our results help in explaining a pattern documented by Calomiris and Nissim (2007). They show that BHCs that have lower than predicted market-to-book ratios (compared to an estimated model) tend to experience large, statistically significant, predictable increases in market values in subsequent quarters. They also investigate whether the predictable changes in stock prices reflect priced risk factors and find that they do not. Our results lend support for the view that future increases in market value in response to a large undervaluation signal are caused by corrective actions taken by managers.

Moreover, the identified support for the influencing hypothesis is a lower bound of the overall corrective behavior. The key identification problem here is that stock returns reflect news about (expected) fundamentals. Expected changes in fundamentals will lead to a spurious relationship between current signals and future values of bank strategic variables in the opposite direction of the influencing hypothesis. For example, a current valuation signal may be an indication that investors worry about future cash flows and profitability, whereas influencing implies that managers take actions to improve profitability after a negative valuation signal. In general, we find evidence for corrective behavior as risk signals lead to more prudent behavior and undervaluation leads to improved performance. If it would be a reflection of fundamentals, it would go in the other direction (as for example the increase in non-performing loans following a risk signal). As the two effects are difficult to disentangle empirically, we prefer emphasizing the finding of influencing, rather than focusing on the magnitude of the impact of influencing.[16]

[16] Another reason why we focus on the significance rather than the magnitude of the influencing effect is a potential bias in the adjustment coefficients in dynamic models. The coefficients on the lagged dependent variable may be upward biased in the absence of a fixed effect and downward biased in the presence of a fixed effect. To address this issue, one typically resorts to dynamic panel data estimators with internal instruments (Blundell and Bond (1998)). However, our modelling setup is different and uses a long lag structure (of eight quarters) to allow for the slow implementation and visibility of managerial decisions. As it is more complex to cast this in the Blundell-Bond setup, we refrain from doing so. Consequently, the level of the adjustment coefficients might be biased, but a statistical difference between the different states (presence or absence of risk/valuation signals) can still be interpreted as evidence of influencing."

4 Direct or Indirect Influencing?

Some caution is necessary in the interpretation of our evidence of market discipline. As mentioned in Flannery (2001) and Federal Reserve System (1999), market influencing has two components. Direct market influence means that a certain stakeholder can assess the riskiness of bank holding companies (market monitoring) and induce bank managers to change their risk behavior (market influencing) in their interest. Indirect market discipline means that the change in bank behavior is enforced by other stakeholders (e.g. supervisors) than the stakeholder exerting the monitoring effort (see also Curry, Fissel, and Hanweck (2008)). In our case, indirect market discipline would then only be partly based on stock market information. For example, managerial decisions could be taken in response to supervisory intervention, which could itself be triggered by stock market signals. Disentangling direct from indirect influence is probably the most daunting task in the market discipline literature and probably requires a setup of a (controlled or natural) experiment or full access to all actions (formal/informal) taken by the supervisor. In the absence thereof, we cannot completely rule out that our findings of market discipline are evidence of indirect influencing. Nevertheless, we believe that we can exclude several potential channels of indirect influence.

4.1 Regulatory Interventions

We are not able to compare the timeliness and accuracy of regulatory bank assessments against market evaluations, as in Berger, Davies, and Flannery (2000) or Evanoff and Wall (2002). However, as a first attempt to mitigate the impact of indirect discipline exerted by supervisors, we check whether or not there were regulatory interventions by the Federal Reserve or FDIC (as listed on their respective websites). One of the best known supervisory interventions is Prompt Corrective Action (PCA) enacted by the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991. FDICIA established capital ratio zones that mandate PCA but also allow for discretionary intervention by regulators. This would allow us to distinguish between direct influence (the amount of influencing when no PCA takes place) and indirect influence (the strength of the market signal over and above the supervisory intervention). We find, however, that there were very few enforcements or interventions[17], hence our signals are unlikely to be proxies for these regulatory

[17] The FDIC provides on its website a list of all enforcement decisions and orders against FDIC-insured institutions. Similar information on PCAs with respect to Bank Holding Companies is provided by the Federal Reserve on their website. Hence, we are able to withdraw information on all past PCAs, either for the BHC or for the underlying commercial banks. Overall, we find 72 records in the FDIC database, of which 67 are PCA proscriptions, 5 PCA dismissal of Officers or Directors and 9 PCA Submission of Capital Plans. However, only 38 of the 72 PCAs take place during the sample period in this paper

interventions. Next to discretionary intervention by regulators, FDICIA also defines thresholds on three capital ratios which may trigger automatic PCA if banks are undercapitalized. We find also these to be rare events[18]. Moreover, given that we allow the target and adjustment speed to be different for significantly undercapitalized banks, we believe that this is not driving our results. Nevertheless, there is still a need for caution as unobserved actions (or other interventions) by the supervisory authorities[19] may still affect bank behavior.

4.2 Subordinated Debtholders

The majority of studies on market discipline look at subordinated debt[20] to infer evidence of monitoring and influencing. The reason is that subordinated debtholders have a concave claim on the value of the bank. Thus, the price of subordinated debt will be informative about the probability of left-tail outcomes, and subordinated debtholders[21] will have strong incentives to monitor and curb bank risk-taking. Using subordinated debt prices, most studies tend to find no response in bank behavior when the price of subordinated debt changes (Krishnan, Ritchken, and Thomson (2005)). This could be interpreted in two ways. On the one hand, it may indicate a failure to find evidence of market influencing, possibly because the choice of issuing subordinated debt is endogenous. Most likely, only safer banks, or banks with a conjectured support of a safety net, will issue subordinated debt. On the other hand, the mere presence of subordinated debt may be sufficient to discipline banks and make future signals (i.e. changes in price rather than the first issuance of

(1991-2007). These 38 PCAs take place in 20 distinct financial institutions. 14 of these institutions are not a member of a bank holding company. Only three banks are member of a one-bank holding company. With respect to the financial insitutions under supervision by the Federal Reserve, we find 27 PCAs in the period 1991-2007. However, only 6 of them (in 5 distinct institutions) took place during our sample period.

[18]In our sample, we observe 91 bank-quarter observatios in which a BHC is categorized as undercapitalized. 41 of these breaches occur in 1991 and 1992. As of 1993, we observe on average less than one bank per quarter that is forced to take a prompt corrective action.

[19]In addition, the (financial) market structure and supervision structure are jointly determined (Masciandaro and Quintyn (2008)).

[20]For example, Ashcraft (2008), Flannery and Sorescu (1996), Goyal (2005), Sironi (2003), Balasubramnian and Cyree (2011), Evanoff and Wall (2002), and Blum (2002).

[21]Subordinated debt, which is typically used in studies of market discipline, is junior to insured debt and senior to equity. Subordinated debtholders give credit to shareholders for the portion of risk shifted past them to the senior claimant (insured depositors and hence the guarantor). Levonian (2001) documents that subordinated debt therefore has features of both sources of funding. Hence, he claims that (changes in) subordinated debt prices reveal two pieces of information about the bank: Info on market value of assets and asset volatility. Exactly the same information can be obtained from bank stock prices and for a larger sample of banks.

subordinated debt) uninformative.

< Insert Table 3 around here >

Therefore, we examine the presence of influencing in the subsets of BHCs with and without outstanding subordinated debt. Summary statistics on the bank characteristics in both subsamples are reported in Table 3. Banks in both samples differ significantly from each other in almost all dimensions. The results of the influencing tests for both subpopulations are reported in Table 4.

< Insert Table 4 around here >

The general finding is that we obtain somewhat stronger evidence of market discipline in the subsample of BHCs *without* subordinated debt. We find weaker support for market influencing in the subgroup of banks issuing subordinated debt. For the latter, the target capital is not significantly different for banks which receive a risk or valuation signal. In the subgroup of banks that have subordinated debt, the target ROE increases from 14% to 16% after a valuation signal, whereas banks without subordinated debt increase this target from 13.2% to more than 17%. A higher target liquidity ratio is observed for banks receiving both signals simultaneously. The influencing results for the subgroup of banks without subordinated debt are indicative for direct influencing, since there can be no contemporaneous action or signal by debtholders. Note also that this sample, which is by definition omitted from most of the previous literature, is also much larger than the set of BHCs with outstanding subordinated debt (see first line of Table 3).

4.3 Retail and Wholesale Depositors

While we can to a significant extent exclude that our stock market based signals coincide with supervisory interventions or pressure from the subordinated debtholders, it may still be that the response following the risk signal is indirect if the pressure would be coming from insured retail (Demirguc-Kunt and Huizinga (2004) and Martinez Peria and Schmukler (2001)) or uninsured wholesale depositors (Calomiris and Kahn (1991), Huang and Ratnovski (2011)). We observe that the share of retail funding in total funding is larger for banks receiving a joint valuation and risk signal (especially for banks without subordinated debt). Hence retail depositors run to the bank, rather than disciplining banks. This finding is in line with Acharya and Mora (2012)'s liquidity backstop argument. The banking system seems to act as a stabilizing liquidity insurer, and actively seeks for deposits via managing deposit rates. Furthermore, we do not find evidence that a BHC is more likely to observe a decrease in the amount of wholesale deposits in response to a risk signal. In particular, we estimate a probit model[22] that relates the probability of observing a reduction in wholesale deposits over a horizon of eight quarters to obtaining a market signals at the beginning of that eight quarter period. We do not find that a risk and/or valuation signal significantly increases the probability of a deposit outflow. We interpret the latter as the absence of a run by uninsured wholesale financiers (in contrast to what happened to some banks in the recent crisis).

4.4 Risk versus Market-to-Book

We explore two dimensions of bank performance: risk and value. While bank risk is of interest to many stakeholders (especially debtholders, regulators and depositors), stock market investors also care about the long-term value of the bank. In particular, they care about the value of the bank relative to a peer group of banks (that is why we use MTB signals conditional on a large set of bank characteristics). As no other stakeholder is harmed by a low valuation, especially if there is no contemporaneous risk signal, a response to a MTB signal (upper right cell of the two-by-two matrices in Table 2) can be interpreted as influencing in favor of the stakeholder who is giving the signal (hence direct influencing). The results in Table 2 convincingly show that there are significant relationships between an undervaluation signal (MTB is substantially lower than its peers; i.e. residual is situated in the lowest decile) and future changes in strategic bank variables. This can be interpreted as evidence of direct influencing in response to a valuation signal by bank equityholders.

As an extension, we also examine what happens when the bank managers get a positive valuation signal. For example, they may also become lax after positive signals and try to maximize their own benefits. To that end, we alter the setup of influencing and allow for a risk signal, a negative valuation signal and a positive valuation signal (results are available upon request). We find mixed evidence of slack or lax behavior after receiving positive signals. Getting a positive valuation signal does not affect the target levels, but does lead to more sluggish adjustments of the capital and liquidity ratios. Hence, the main difference between the negative and positive valuation signals is that the former lead to faster adjustment to a new target, whereas the latter only leads to slower adjustment to the same target.

4.5 Stock prices versus subordinated debt yields

Apart from a new testing strategy, this paper differs from many other studies on market discipline because it infers evidence on market monitoring and influencing from stock prices (as in Curry, Fissel, and Hanweck

[22] The additional results referred to in this subsection are available upon request.

(2008)), rather than from subordinated debt (e.g., Ashcraft (2008), Flannery and Sorescu (1996), Goyal (2005), Sironi (2003) or Krishnan, Ritchken, and Thomson (2005)). This is motivated by at least three reasons. First, while bank risk is of interest to many stakeholders (especially debtholders, regulators and depositors), stock market investors also care about the long-term value of the bank. A response to a valuation signal can be interpreted as direct influencing in favor of the stakeholder who is giving the signal, as no other stakeholder is harmed by a low valuation (especially if there is no contemporaneous risk signal). Second, subordinated debtholders have a concave claim on the value of the bank. Equityholders, on the other hand, have a convex claim on banks' assets, which may cause risk-shifting incentives (Jensen and Meckling (1976)). However, this need not be beneficial to stockholders if the charter value is eroded. Park and Peristiani (2007) show that there is a distinct convex nonlinear relationship between the market-to-book ratio and bank risk. Based on their empirical tests, they conclude that for publicly held US BHCs, the interests of bank stockholders are aligned with those of regulators and debtholders (except for a small subset of extremely risky ones). Stockholders penalize riskier strategies to preserve charter value. Only when the option value becomes large enough to compensate for the loss of charter value, stockholders elect instead to reward risk-taking to further increase the put option value, but this only happens for a very small portion of their sample. Third, in comparison with subordinated debt, stock prices are available for a larger sample of banks (see first line of Table 3). In addition, according to Kwan (2002), stock market data have an advantage over bond market data in terms of higher quality. Stock market data are more likely to timely incorporate information than bond prices, because stocks are traded more frequently, are easier to short, and because they are followed by more professional analysts than bonds. Hence, we extend the test of market disciplining to the sample of BHCs that do not have outstanding subordinated debt. This allows us to examine whether the lack of empirical support for market discipline is due to the sample under consideration, the risk signal (subordinated debt prices versus stock prices) or both.

Tying this evidence together, we conclude that banks respond to risk and value signals by equityholders. Moreover, it is unlikely that other stakeholders give contemporaneous signals, which reinforces the case in favor of direct influencing. Moreover, we find that banks shift to less risky activities in response to a volatility signal, even though equityholders have a convex payoff function and may like risk. Moreover, this claim is even more convincing in the case where there is both a risk and valuation signal. In these situations, equityholders strongly indicate that the bank is taking risks for which they are not compensated and banks react accordingly.

5 Which banks are more likely to get signals?

We now investigate in more detail which characteristics make it more likely that a bank will receive a risk or valuation signal. Recall that these signals are based on the extreme inefficiency scores (risk signal) or residuals (valuation signal). All else equal, banks for which the variance of the inefficiency scores or residuals is larger, will have a higher chance of receiving a risk or valuation signal. Therefore, we investigate which bank characteristics drive the variance of the risk inefficiencies or market-to-book residuals. For the semi-volatility setup, we add scale heterogeneity to the stochastic frontier model. For the market-to-book ratio, we use a regression model with multiplicative heteroscedasticity as in Harvey (1976).[23] We make the variance a function of time-varying bank-specific characteristics $Z_{i,t}$, such that $\sigma^2_{u_{i,t}} = \exp(\delta_0 + \delta Z_{i,t})$. We use the exponential function to guarantee that the variance is positive. A positive and significant δ implies that bank characteristics $Z_{i,t}$ increases the variance. A larger variance makes a larger risk inefficiency score or MTB residual, which may lead to influencing, more likely. Therefore, we consider this dispersion or variance to be the scope for pressure or signals coming from stock market investors conditional on their assessment of banks' risk and value profiles. We hypothesize and test whether or not this pressure by stock market investors is related to (1) complexity, (2) managerial discretion, and (3) opaqueness. We motivate each of these variables individually and discuss the estimation results in parallel.

5.1 Complexity: Funding, asset and revenue composition[24]

In complex, diversified firms such as large BHCs, determining the financial condition of a conglomerate might be harder compared to assessing the financial strength of a specialized firm. Diversification of activities might, however, also yield more risk-efficient banks if the shocks to the different types of activities are imperfectly correlated (Laeven and Levine (2007)). Hence, one view is that equityholders use less discretion as they expect shocks to different activities to cancel out. The other is that more diversified banks may be harder to monitor as they leave more scope for managerial discretion. We include Hirschman Herfindahl indices (HHI) of specialization in each of the core activities of banks: a HHI for diversification in funding (deposit diversification), a HHI for loan diversification, a HHI for revenue diversity in general (the mix between interest and non-interest income) and a HHI capturing diversity of four non-interest income components. A

[23] Recently, Cerqueiro, Degryse, and Ongena (2011) use a similar model to analyze the dispersion in interest rates on loans issued to small and medium-sized enterprises.

[24] Although the stochastic frontier model with scale heterogeneity or the multiplicative heteroscedastic regression model is modelled in one step, the results are discussed in two steps.

higher value of the HHI indicates that a bank has a more focused orientation[25]. Lower values point to more diversification. As the two effects of complexity work in opposite directions, we include earnings volatility to control for the risk reduction generated by portfolio diversification. If the portfolio risk-reduction view holds, we should find that more stable profits (potentially caused by combining imperfectly correlated activities) lead to a lower variance. In addition, BHCs may alter their scope either by restructuring their activities or by expanding their size. We include loan growth to control for banks' overall expansion strategies. A high growth rate might indicate that banks expanded via mergers and acquisitions or attracted a new pool (of probably more risky) borrowers[26].

< Insert Table 5 around here >

The estimation results can be found in Table 5. The variance of total risk inefficiency is positively related to specialization. This indicates that, from a monitoring perspective, the portfolio effects of diversification more than compensate the cost of increased complexity that diversification may entail. Note that this effect is not only statistically, but also economically significant. A one standard deviation increase in income specialization increases the dispersion of total risk with 16.2%.

A higher loan growth rate leads to a larger variance in the valuation of BHCs. Hence, an expansionary strategy makes it more difficult to assess the true value. More stable earnings, reflected by a lower ROE volatility, lead to a lower dispersion in total risk inefficiency scores as well as in the residual variance of the market-to-book ratio. For instance, a one standard deviation increase in ROE volatility leads to an increase in the variance of (risk) inefficiency of 25%. This suggests that the preference equityholders have for stable revenue streams dominates the potential negative effects that earnings smoothing and managerial discretion may have on their ability to assess the situation of the bank. However, volatility of profits is only

[25] The general formula of the Hirschman Herfindahl index is $HHI_{i,t} = \sum_{j=1}^{J} \left(\frac{X_{i,j,t}}{\sum_{j=1}^{J} X_{i,j,t}} \right)^2$ and is the sum of the squared activity shares (i is a bank indicator, t is time and j=1,...,J refers to the activities over which one measures specialization/diversification). We compute four different HHI-measures: a HHI for diversification in funding (J=3, Noninterest Bearing Deposits, Interest Bearing Core Deposits and Wholesale funding), a HHI for loan diversification (J=5, C&I Loans, Real Estate Loans, Agriculture Loans, Consumer Loans, Other Loans), a HHI for revenue diversity in general (J=2, interest and non-interest income) and a HHI capturing diversity of the four non-interest income components (J=4, Fiduciary Activities, Service Charges on Deposits Accounts, Trading Revenue, Other Non Interest Income).

[26] For example by an expansion into subprime loans (see e.g. Knaup and Wagner (2012)) or by increasing the share of difficult-to-value Level III assets. Unfortunately, these conjectures cannot be tested in our sample as (i) the build up of subprime loans only happened in the latter sample years and (ii) reporting the amount of "Level 3 fair value measurements of loans and leases" (item bhckf245) only became compulsory in the last year of our sample (more precisely as of 2007-03-31).

a crude proxy of managerial discretion and earnings smoothing. As emphasized in Hirtle (2007), disclosure plays an important role in market discipline since market participants need to have meaningful and accurate information on which to base their judgments of risk and performance.

5.2 Managerial Discretion and Earnings Forecast Dispersion

We measure disclosure in a qualitative sense and focus on the extent to which bank managers have discretion in reporting certain accounting items, with a potential impact on the bank's perceived value and risk profile. We hypothesize that the variance of the inefficiency term will be larger for banks with more discretion in earnings reporting.

To empirically investigate this hypothesis, we test whether or not bank-specific volatility, $\sigma^2_{u_{i,t}}$, of either the MTB residual or the risk inefficiency term, is increasing in measures of managerial discretion. Managers can both over- and underprovision for expected loan losses and either postpone or prepone the realization of securities gains and losses. As in Beatty, Ke, and Petroni (2002) and Cornett, McNutt, and Tehranian (2009), we measure discretionary loan loss provisions by regressing[27] loan loss provisions on total assets, non-performing loans, loan loss allowances and the different loan classes. The discretionary component of loan loss provisioning is the absolute value of the error term of this regression. Similarly, the discretionary component of realized security gains and losses is the absolute value of the error term of the regression of realized security gains and losses on total assets and unrealized security gains and losses. If managers use more discretion in loan loss provisioning and realizing trading gains, the residuals of these models will be larger. Both point to discretion in earnings management which may obscure true performance. While unexpected loan loss provisions and security gains and losses may make bank performance more difficult to assess, it is often used to smooth earnings over time (Laeven and Majnoni (2003)).

Secondly, we relate the volatility of the SV inefficiency term and the MTB residual to opaqueness, measured by the dispersion in analysts' earnings per share (EPS) forecasts. This measure is widely used in the accounting literature to measure firm transparency (see e.g. Lang, Lins, and Maffett (2012)), as well as in the banking literature by Flannery, Kwan, and Nimalendran (2004) who compare the opaqueness of US bank holding companies with similar-sized non-banking firms. We obtain the earnings forecast data from the Institutional Brokers Estimate System (IBES). We calculate the dispersion measure on a quarterly basis as the cross-sectional dispersion in the most recent forecast of all analysts that made their prediction within

[27] Results from these regressions are available upon request.

the last year. We include only the analysts' last forecasts and require this forecast to be made in the 4 quarters prior to the end of the quarter to avoid that stale forecasts would bias our dispersion measure. To avoid the documented downward bias in forecasted EPS induced by the way IBES adjusts for stock splits, we closely follow the adjustment method described in Diether, Malloy, and Scherbina (2002) and Glushkov and Robinson (2006). Finally, we only include the quarterly dispersion measure if at least two separate analyst forecasts are available. After applying the different filters, we end up with a dataset consisting of 495 banks[28] and 8271 bank-quarter observations. The average number of analyst forecasts per bank per quarter is a satisfying 9.04.

The estimation results are presented in Table 5. We not only include the managerial discretion and earnings forecast disagreement measures, but also loan growth, ROE volatility and the different complexity indicators. It is comforting that the results for those variables are very similar in the reduced sample compared to the full sample. With respect to management discretion, we find that stock market investors exert more pressure in their assessment of risk for banks exhibiting a high discretionary behavior in the realization of securities gains/losses. A one standard deviation increase in this discretion measure leads to a 14% increase in the dispersion of total risk inefficiencies. Discretionary behavior in loan loss provisioning also matters for risk, but to a lesser extent. However, the main goal of active discretion in loan loss provisioning is earnings smoothing, which is considered favorably (i.e. stable profit streams lead to a lower variance of the MTB residuals and the SV inefficiencies). In fact, the leeway managers permit themselves in dealing with problem loans leads to more pressure by bank equityholders in their assessment of bank value. Dispersion in IBES analyst forecasts unambiguously increases the variance of both signals. This not only suggests that banks differ substantially in their degrees of opaqueness, but also that stock market investors take these differences into account. The dispersion in total risk inefficiencies increases by 17.7% (12.4% for MTB residuals) in response to a one standard deviation increase in analyst forecasts dispersion.

[28] We lose a significant number of bank-quarter observations when matching the existing dataset with IBES data. Both datasets are merged as follows. The main identifier in IBES is the IBES ticker, whereas the main identifier in CRSP is the permno of the bank. Hence, in order to merge the information of both files, the best approach is to use common secondary identifiers to construct a linking table that relates the permno of the bank to the IBES ticker. We follow the procedure proposed by WRDS (Moussawi (2006)), which assigns a score to each match, according to the quality of the link.

6 Conclusion

The financial crisis of 2007-09 has illustrated that the choice of business models and (lack of) transparency in banking may have profound consequences for the risk profile of the banks. Even within certain bank business models, we noticed a large discrepancy of banks' vulnerability to adverse shocks. The question we address is whether or not information about BHC risk and valuation can be extracted from stock market information and whether or not market signals are sufficiently strong to force banks to alter their risk and performance profile. These are the two faces of market discipline: monitoring and influencing. If the stock market is able to monitor bank risk, this information is useful for supervisors and they should include market-based risk indicators in their information set. If the stock market is able to influence bank risk behavior, this can be complementary to supervisory actions and reinforce them. In this paper, we develop an empirical setup to examine the ability of stock market investors to monitor and influence bank risk and performance in a sample of US BHCs over the period 1991-2007.

We investigate the influencing hypothesis by analyzing if and to what extent bank managers react to risk and valuation signals from the stock market over a medium to long-run horizon. The hypothesis is that banks exhibiting a relatively high degree of risk inefficiency will respond by taking remedial action in order to adjust their risk profile. Similarly, banks that are judged to underperform relative to their peers are expected to alter their cost and revenue structure to improve bank value. In contrast to most of the extant literature, we do find evidence of stock market influencing in US banking. Banks that receive a risk signal react by increasing their capital buffer and lowering their liquidity risk. These actions are in line with predictions and with the objective of supervisors. Banks receiving a negative valuation signal react by increasing their target profit level, primarily by lowering the cost-to-income ratio, indicating that most of the performance improvement is intended to come from the cost efficiency side. Hence, these corrective actions taken by managers in response to a large undervaluation signal may lead to future increases in market value, which may explain the finding by Calomiris and Nissim (2007) that BHCs that have lower than predicted market-to-book ratios (compared to an estimated model) tend to experience large, statistically significant, predictable increases in market values in subsequent quarters. Finding evidence of influencing in this setup is indicative for a type of market discipline that Bliss and Flannery (2002) label "more benign and commonplace" compared to, e.g., a distressed takeover, outright defaults or executive turnovers.

Next to investigating the response to risk and valuation signals, we also analyze which banks are more likely to get signals. We find that stock market investors punish discretionary behavior, especially in the case of security gains and losses. More unpredictable banks exhibit larger deviations in terms of risk and valuation. We also find strong evidence that the degree of opaqueness is positively related to the variance of the risk inefficiencies and valuation residuals. Regulation should be designed to lower the degree of discretion that bank managers can exercise. A reduction in the opacity of banks can be achieved by fostering information disclosure, e.g. through a timely and accurate publication of relevant on and off balance sheet risk exposures. Providing better information may allow banks to avoid large random stock market penalties in terms of risk or valuation. Hence, one set of results indicates which banks are more likely to receive a risk and/or valuation signal. The other set of results provides insight in how a bank responds to a signal. It might be an interesting avenue for further research to combine these. In particular, it may be interesting to analyze the extent to which influencing (i.e. the impact of risk/valuation signals on the target or speed of adjustment) varies with the transparency or opacity of the bank.

To rule out that our results are driven by indirect influencing, we also investigate the contribution of other potential monitors, such as subordinated debtholders, retail and wholesale depositors and supervisors. We find that regulatory enforcement actions are unlikely to explain our results, that influencing is most pronounced in banks without subordinated debt and that wholesale depositors are not reacting to our risk signals. Nevertheless, as in most other studies addressing this issue, there is a need for caution since other sources of discipline, such as unobserved actions taken by the supervisory authorities, may affect bank behavior.

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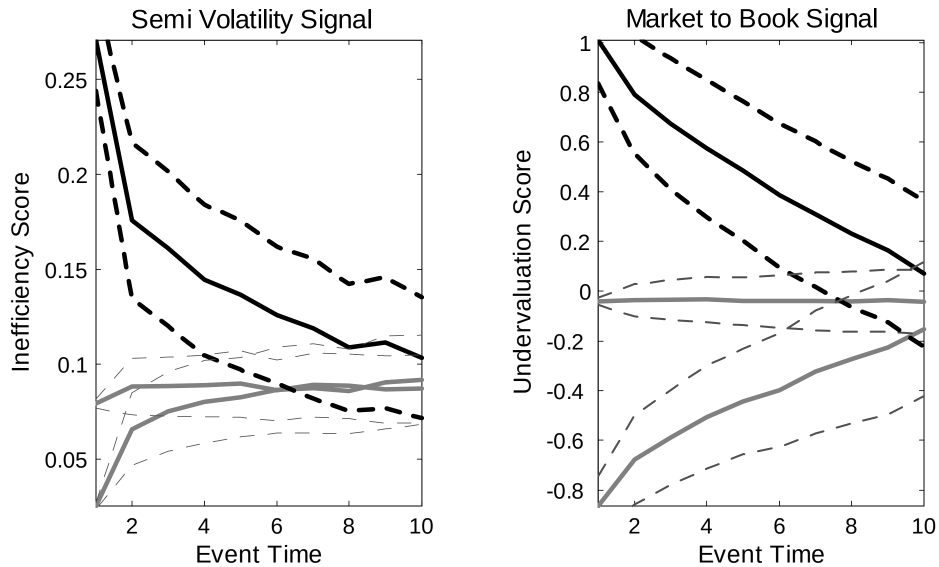
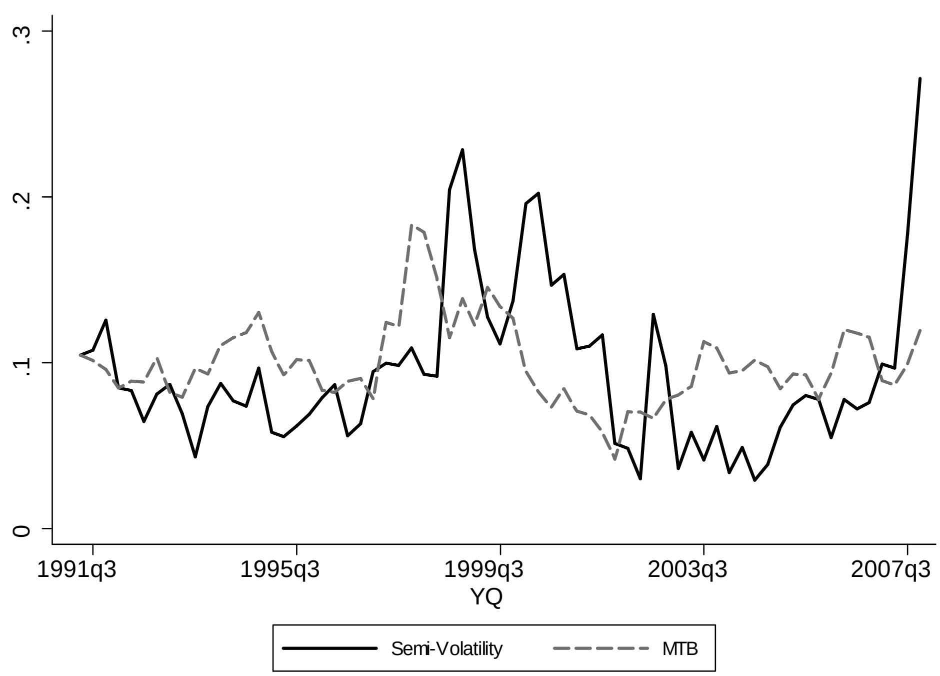
Figure 1: Dynamic Behavior of the Risk and Valuation Signals

Panel A: Level and dynamics of efficiency scores



Panel B: Time series of Frequency of Signals



The upper panel consists of two subplots, one for the risk signal and one for the market-to-book signal. Each subplot presents the average inefficiency score or extent of misvaluation of three portfolios in event time. Each quarter, we sort BHCs into deciles according to the size of the signal. The portfolio formation quarter is denoted time period 1. We then compute the average signal size for each portfolio in each of the subsequent 10 quarters, holding the portfolio composition constant (except for BHCs that exit the sample). We repeat these two steps of sorting and averaging for every quarter in the sample period (1993-2007). This process generates 60 sets of event-time averages, one for each quarter in our sample. We then compute the average signal size of each portfolio across the 60 sets within each event quarter. The most extreme decile (highest risk or lowest value) is indicated by the thicker red line. The least extreme decile as well as the two middle deciles (combined in one portfolio) are indicated in black. The dashed lines surrounding the portfolio averages represent 90 per cent confidence bounds. They are computed as the average standard error across the 60 sets of averages (Lemmon et al., 2008). The lower panel provides information on the fraction of banks receiving a signal in a given quarter. A bank is said to receive a signal if the inefficiency score of the bank at time t is among the 10 per cent worst inefficiency scores (of all banks) observed over the preceding four years.

Table 1: Summary Statistics of Variables Used in the Analysis of Bank Monitoring

Variable	Mean	Std. Dev.	Min.	Max.	N
PANEL A					
Valuation and risk metric based on banks' share price					
Semi volatility	0.2972	0.1342	0.1026	0.8426	17264
Market-to-Book Value of Equity	2.3758	1.1545	0.5196	7.2331	17216
PANEL B					
Bank Strategy Variables					
ln(Total Assets)	15.0901	1.5793	12.194	19.7077	17264
Tier 1 Risk-Based Capital Ratio	11.7388	3.1518	6.2556	27.72	17264
Non-Performing Loans Ratio	0.0114	0.013	0	0.0853	17264
Cost to Income	0.6384	0.12	0.3732	1.188	17264
Return on Equity	0.0324	0.0179	-0.0836	0.0686	17264
Liquid Assets	0.0455	0.0909	-0.1711	0.3711	17264
Funding Structure					
Non-Interest-Bearing Deposits Share	0.1326	0.0704	0.0158	0.391	17264
Interest-Bearing Core Deposits Share	0.6687	0.1123	0.2867	0.8827	17264
Wholesale Funding Share	0.197	0.1052	0.0277	0.5896	17264
Deposits to Total Assets	0.7609	0.1056	0.3603	0.9238	17264
Asset Mix					
Real Estate Loan Share	0.6316	0.1876	0.0653	0.9797	17264
Commercial and Industrial Loan Share	0.1935	0.1185	0.0034	0.6332	17264
Agricultural Loan Share	0.01	0.0208	0	0.1295	17264
Consumer Loan Share	0.1175	0.0999	0.001	0.5009	17264
Other Loan Share	0.0415	0.0592	0	0.3464	17264
Loans to Total Assets	0.6432	0.1209	0.2144	0.8709	17264
Revenue Streams					
Interest Income Share	0.7373	0.1382	0.2487	0.9613	17264
Non-Interest Income Share	0.2627	0.1382	0.0387	0.7513	17264
Fiduciary Activities Income Share	0.0379	0.06	0	0.3835	17264
Service Charges on Deposit Accounts Share	0.0747	0.0369	0.0003	0.1806	17264
Trading Revenue Share	0.006	0.0186	-0.0078	0.1117	17264
Other Non-Interest Income Share	0.1405	0.1139	0.0075	0.6652	17264
Deposit-Loan Synergies					
Deposit Loan Synergies	0.039	0.0306	0.0006	0.2723	17264
Unused Loan Commitments Share	0.1765	0.0957	0.0203	0.536	17264
Transaction Deposits Share	0.2214	0.1084	0.0298	0.5079	17264

This table contains summary statistics on the variables used in the analysis of bank monitoring and consists of two parts. In panel A, we provide information on the equity market-based risk and value measures (the dependent variables). For the calculation of semi-volatility, we take the lower deviation of the daily bank stock returns within a quarter. We then semi-volatility by multiplying with the squared root of 252. We also compute a market-based valuation metric, which is the market value to the book value of tangible common equity. Both variables are measured over the period 1991-2007 on a quarterly basis. Panel B of this table contains information on the independent variables. Bank size is measured as the natural logarithm of total assets expressed in US dollar thousands and deflated to 2007:Q4 values. All other variables are measured as ratios. For detailed information on the exact computation of the ratios, we refer to the Appendix. Income statement data are reported on a calendar year-to-date basis in the FRY9C reports and are therefore converted to quarter-to-quarter changes before computing ratios. The variables are measured over the period 1991-2007 on a quarterly basis. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters. Furthermore, we exclude banks of which the stock has zero trading volume for at least twenty percent of the observations. The final sample consists of 17264 observations on 899 bank holding companies. All variables are winsorized at the 1 percent level.

Table 2: Evidence of market Influencing: The impact of market signals on the Target ratio and Adjustment Speed

		Target Ratio		Adjustment Speed	
		MTB=0	MTB=1	MTB=0	MTB=1
Tier 1 Risk-Based Capital Ratio	SV=0	11.488	10.426***	0.291	0.413*
			0.001		0.064
	SV=1	12.223**	11.441	0.334	0.606***
		0.039	0.927	0.500	0.000
Return on Equity	SV=0	0.034	0.041***	0.539	0.532
			0.000		0.921
	SV=1	0.032*	0.033	0.550	0.515
		0.067	0.802	0.825	0.842
Non-Performing Loans Ratio	SV=0	0.711	0.645	0.562	0.608
			0.220		0.114
	SV=1	0.959***	0.712	0.640	0.730
		0.000	0.989	0.196	0.142
Cost to Income Ratio	SV=0	0.614	0.550***	0.337	0.329
			0.001		0.881
	SV=1	0.663***	0.625	0.294	0.314
		0.007	0.805	0.389	0.852
Liquidity Ratio	SV=0	0.026	0.037	0.230	0.299
			0.249		0.163
	SV=1	0.048*	0.025	0.223	0.157
		0.077	0.975	0.904	0.287
Non-Interest Income Share	SV=0	0.323	0.411	0.147	0.106
			0.216		0.285
	SV=1	0.291	0.322	0.276**	0.309**
		0.117	0.969	0.035	0.031
Dividend Payout Ratio	SV=0	0.390	0.349***	0.571	0.723**
			0.002		0.024
	SV=1	0.379	0.385	0.621	0.572
		0.612	0.907	0.401	0.991

This table contains results on the market influencing tests. We use a partial adjustment model to test whether or not reallocations in strategic bank characteristics occur in response to a risk (SV) and/or valuation (MTB) signal. We focus on the effect on seven strategic bank characteristics: the capital ratio, asset quality (non-performing-loans ratio), cost efficiency (cost-to-income ratio), profitability (ROE), liquidity ratio (the ratio of liquid assets to total assets), the ratio of non-interest income to total income and the dividend pay-out ratio. For each characteristic, we estimate the following equation:

$$\Delta y_{i,t} = \left(\gamma_0 + \gamma_0^* D^y_{i,t-\tau} + \gamma_1 D^{SV}_{i,t-\tau} + \gamma_2 D^{MTB}_{i,t-\tau} + \gamma_3 D^{SV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau}\right) \times \left(y^*_{i,t} - y_{i,t-\tau}\right) + \varepsilon_{i,t}$$

with

$$y^*_{i,t} = \alpha_0 + \alpha_0^* D^y_{i,t-\tau} + \alpha_1 D^{SV}_{i,t-\tau} + \alpha_2 D^{MTB}_{i,t-\tau} + \alpha_3 D^{SV}_{i,t-\tau} \cdot D^{MTB}_{i,t-\tau} + X_{i,t-\tau}\beta$$

For sake of space and clarity, we only report the target level (left panel) and the speed of adjustment (right panel) for the seven indicators. We report the target and adjustment speed in four distinct cases where (1) the bank neither gets a a risk nor valuation signal (dummy SV= dummy MTB=0, the upper left cell), (2) the bank gets only a risk signal (dummy SV=1, dummy MTB=0, the lower left cell), (3) the bank gets only a valuation signal (dummy SV=0, dummy MTB=1, the upper right cell) and (4) the bank gets both a risk and a valuation signal (dummy SV= dummy MTB=1, the lower right cell). This results in fourteen 2 by 2 matrices. In each case, we report the p-value in parentheses to assess the statistical significance of the differences with the benchmark case of no signal, i.e. the upper left cell. Significant differences (w.r.t. to the benchmark case) at the 10, 5 and 1 per cent level are indicated with *, ** and ***, respectively.

Table 3: Summary statistics of a sample split of banks with and without Subordinated Debt

	Subordinated Debt		
	NO	YES	p-value
Number of Observations	4363	1821	
ln(Total Assets)	14.363	16.684	0.000
Tier 1 Risk-Based Capital Ratio	12.886	9.810	0.000
Non-Performing Loans Ratio	0.884	1.042	0.000
Cost to Income	0.624	0.629	0.135
Return on Equity	0.033	0.038	0.000
Liquid Assets	0.088	0.104	0.000
Non-Interest Income Share	0.218	0.348	0.000
Dividend Payout ratio	0.342	0.362	0.000
Subordinated debt/Total Capital	0.000	0.213	0.000
Risk Signal	0.144	0.079	0.000
Valuation Signal	0.100	0.123	0.010
Joint Signal	0.015	0.010	0.209

This table provides summary statistics on bank size, the seven strategic bank characteristics, the amount of subordinated debt in total capital and the frequency of risk signals, valuation signals or joint signals. We compare the means of the variables in the subsamples of banks with subordinated debt (the first column) and bank without subordinated debt (the second column). The third column contains the p-value of the difference-in-mean test for these variables.

Table 4: Target Ratio and Adjustment Speed: Sample split based on Subordinated Debt

		Target Ratio				Adjustment Speed			
		No Sub. Debt		Sub. Debt		No. Sub. Debt		Sub Debt	
		MTB=0	MTB=1	MTB=0	MTB=1	MTB=0	MTB=1	MTB=0	MTB=1
Tier 1 Risk-Based Capital Ratio	SV=0	12.307	11.718*	9.915	9.253	0.324	0.557***	0.441	0.402
			0.050		0.122		0.003		0.682
	SV=1	12.678	12.304	9.876	10.113	0.346	0.679***	0.328	0.626
		0.298	0.996	0.962	0.829	0.769	0.000	0.391	0.417
Return on Equity	SV=0	0.033	0.043***	0.035	0.041***	0.445	0.408	0.672	0.672
			0.000		0.002		0.732		0.994
	SV=1	0.030	0.036	0.033	0.025	0.556*	0.566	0.543	0.283**
		0.178	0.479	0.399	0.339	0.061	0.209	0.217	0.080
Non-Performing Loans Ratio	SV=0	0.678	0.516*	0.740	0.713	0.528	0.565	0.575	0.610
			0.052		0.738		0.515		0.310
	SV=1	0.933***	0.661	1.010*	0.767	0.649**	0.695	0.528	0.690*
		0.000	0.902	0.074	0.884	0.018	0.371	0.776	0.083
Cost to Income Ratio	SV=0	0.627	0.518***	0.609	0.584	0.315	0.270	0.416	0.483
			0.002		0.210		0.599		0.280
	SV=1	0.672**	0.554	0.638	0.725	0.331	0.321	0.245	0.296
		0.021	0.174	0.516	0.184	0.787	0.959	0.140	0.555
Liquidity	SV=0	0.025	0.031	0.012	0.026	0.249	0.340*	0.242	0.293
			0.517		0.487		0.087		0.478
	SV=1	0.043	-0.105	0.038	0.077**	0.213	0.066**	0.339	0.404
		0.206	0.495	0.335	0.013	0.565	0.021	0.362	0.204
Non-Interest Income Share	SV=0	0.262	0.255	0.330	0.414	0.215	0.237	0.138	0.131
			0.842		0.113		0.798		0.882
	SV=1	0.242	0.270	0.388	0.388	0.352	0.375	0.306	0.229
		0.183	0.791	0.197	0.305	0.137	0.142	0.101	0.449
Dividend Payout Ratio	SV=0	0.389	0.337***	0.383	0.343**	0.509	0.684	0.686	0.786
			0.009		0.026		0.119		0.234
	SV=1	0.373	0.393	0.360	0.327	0.598	0.677	0.698	0.431
		0.579	0.950	0.535	0.314	0.245	0.412	0.891	0.120

This table provides information on whether the evidence for market influencing is different in the subsample of banks without subordinated debt holders, versus banks with subordinated debt holders. We assess whether reallocations in strategic bank characteristics occur in response to a risk (SV) and/or valuation (MTB) signal, by means of a partial adjustment model. We focus on the effect on seven strategic bank characteristics: the capital ratio, asset quality (non-performing-loans ratio), management quality (cost-to-income ratio), earnings (ROE), liquidity ratio (the ratio of liquid assets to total assets), the ratio of non-interest income to total income and the dividend pay-out ratio. For each characteristic, we estimate equation (3). For sake of space and clarity, we only report the target level (left panel) and the speed of adjustment (right panel) for the seven indicators. We report the target and adjustment speed in four distinct cases where (1) the bank neither gets a risk nor valuation signal (dummy SV=dummy MTB=0, the upper left cell), (2) the bank gets only a risk signal (dummy SV=1, dummy MTB=0, the lower left cell), (3) the bank gets only a valuation signal (dummy SV=0, dummy MTB=1, the upper right cell) and (4) the bank gets both a risk and a valuation signal (dummy SV=dummy MTB=1, the lower right cell). We report the results for both the subsample without subordinated debt and with subordinated debt. In each case, we report the p-value in parentheses to assess the statistical significance of the differences with the benchmark case of no signal, i.e. the upper left cell. Significant differences (w.r.t. to the benchmark case) at the 10, 5 and 1 per cent level are indicated with *, ** and ***, respectively.

Table 5: Which banks are more likely to get signals: complexity and opacity

VARIABLES	Mean *Std. Deviation*	(1) Full Sample Semi Volatility SFA scale	(2) Reduced Sample Semi Volatility SFA scale	(3) Full Sample Market-to-Book (Equity) Cond. Het. regression scale	(4) Reduced Sample Market-to-Book (Equity) Cond. Het. regression scale
Volatility of ROE	0.0081	0.251***	0.116***	0.224***	0.220***
	0.0096	(0.0136)	(0.0238)	(0.0445)	(0.0647)
Loan Growth	0.1304	-0.0210	0.0235	0.129***	0.166***
	0.1528	(0.0131)	(0.0191)	(0.0430)	(0.0619)
Funding Specialization	0.5352	0.0535***	-0.00997	-0.100	-0.120
	0.0922	(0.0156)	(0.0239)	(0.0613)	(0.0817)
Loan Portfolio Specialization	0.5234	0.0238	0.0685***	-0.0305	-0.0335
	0.1605	(0.0170)	(0.0246)	(0.0777)	(0.101)
Income Specialization	0.652	0.162***	0.116***	-0.346***	-0.250***
	0.0976	(0.0159)	(0.0242)	(0.0665)	(0.0884)
Specialization in non-traditional, non-interest	0.4901	0.155***	0.157***	0.347***	0.412***
income generating activities	*0.1389*	(0.0157)	(0.0227)	(0.0633)	(0.0794)
Dispersion in IBES analyst forecasts	0.0704		0.177***		0.124***
	0.1232		(0.0184)		(0.0381)
Discretion in loan loss provisioning	0.0132		0.0412**		0.129***
	0.0246		(0.0178)		(0.0429)
Discretion in realizing security gains and losses	0.0374		0.139***		0.0655
	0.0645		(0.0220)		(0.0435)
Constant		-4.108***	-4.537***	-1.408***	-1.378***
		(0.0210)	(0.0313)	(0.0715)	(0.0863)
Observations		17264	8271	17216	8249
Standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

In this table we provide the estimation results for the scale heterogeneity in the stochastic frontier model and the conditional heteroscedastic regression model, where the volatility of the inefficiency term is related to two sets of variables. In the Full Sample, the bank-specific volatility of the inefficiency term is related to the complexity or specialization of the banking firm. We use Hirschmann-Herfindahl indices of specialization or diversification regarding funding, activity mix as well as revenue sources. The higher the value of the index, the more the bank is specialized in that area. We also include the past loan growth and the volatility of the ROE as independent variables. In the Reduced Sample, we introduce the dispersion in IBES analyst forecast as a measure of bank opaqueness and proxies for various aspects of (discretion in) (earnings) management, such as discretion in loan loss provisioning and the realization of securities gains and losses and earnings volatility. In the first column, we report for each variable the mean (first line) and its standard deviation (second line, in italics).

A Online Appendix - Monitoring Bank Risk and Equityholder Value

An essential first step in our test for market influencing is to establish a relationship between bank-specific risk and performance measures and various (lagged) bank-specific characteristics, this within either a stochastic frontier (risk) or linear regression (valuation) framework. The extensive literature on market monitoring, which shows that securityholders indeed distinguish between banks with different risk profiles, provides good guidance on which proxies to include (see e.g. Flannery and Sorescu (1996), Saunders, Strock, and Travlos (1990), Stiroh (2004), Stiroh (2006b), Hirtle and Stiroh (2007)). To allow comparison with existing studies and to be transparent with respect to the other steps of the analysis, we briefly describe in this appendix the results of the baseline equation. While not the main contribution of this paper, we believe we still add to this literature by considering a more comprehensive range of bank characteristics which affect a bank's business model. To assess how potential differences in the banks' composition of assets, liabilities and operational characteristics are reflected in bank risk and value, we relate SV (Semi-Volatility) and MTB (Market-to-Book) to four sets of bank characteristics, proxying for: (i) overall bank strategy, (ii) the bank's funding structure (Calomiris and Nissim (2007), Demirguc-Kunt and Huizinga (2010), Hirtle and Stiroh (2007)), (iii) asset mix (as e.g., Calomiris and Nissim (2007), Morgan and Stiroh (2001)), and (iv) revenue diversity (as e.g., Stiroh (2006), Stiroh (2006b), De Jonghe (2010)), as well as variables proxying for deposit-loan liquidity synergies (Gatev, Schuermann, and Strahan (2009)). Our vector $X_{i,t}$ of bank-specific characteristics, which appears in Equation (1) in the paper, is hence given by:

$$X_{i,t} = [\mathit{Bank\ Strategy},\ \mathit{Funding\ Structure},\ \mathit{Asset\ Mix},\ \mathit{Revenue\ Streams}]_{i,t} \tag{A.1}$$

Summary statistics are reported in Table 1 of the paper. All data are collected from the publicly available FR Y-9C reports. The definition and construction of each variable is described in Appendix B. Consequently, we link the FR Y-9C reports to banks' stock prices using the match provided on the Federal Reserve Bank of New York website[29]. Controlling for a large set of bank characteristics is important for our tests of market influencing. Both the magnitude and the accuracy of the risk and valuation signals, and hence the accuracy of our test of market influencing, will depend to a great extent on the quality and level of the bank-specific characteristics included in either the stochastic frontier (SV) or linear regression (MTB) model.

Our sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters in the period 1991-2007. The total sample consists of 17,264 observations on 899

[29] http://www.ny.frb.org/research/banking_research/datasets.html

bank holding companies. Our sample period covers two full business cycles as well as a number of stressed periods.[30] The impact of these events and the business cycle is captured by time fixed effects. We now motivate the bank-specific variables and their effect on risk and value group by group. The discussion is based on the estimation results reported in the first two columns of Table A.1, which correspond with a model without conditional variance. In columns 3 and 4, we report the results of a model with conditional variance (as used in Section 5 of the paper). We only refer to the latter results in the few cases where they differ from the former.

< Insert Table A.1 around here >

To facilitate the economic interpretation of the coefficients, we standardize all independent variables. Bank fixed effects are included in all estimations.

Bank Strategy Variables The bank-specific proxies for overall bank strategy capture strategic choices made by bank managers that may affect a bank's risk and valuation profile. We include the regulatory Tier 1 capital ratio[31] and the liquid-to-total-assets ratio to incorporate the possibility that better capitalized and more liquid institutions may be less vulnerable to shocks. Asset quality is measured by the ratio of loans past due 90 days or more and non-accrual loans to total loans. We also include the cost-to-income ratio as a measure of cost efficiency. This ratio measures the overheads or costs of running the bank as a percentage of total operating income before provisions. Finally, we include (the log of) bank size[32] as larger banks may diversify their risk more and may enjoy economies of scale (Hughes, Mester, and Moon (2001)), and bank profitability (ROE) to control for a risk-return trade-off. The first part of Table A.1 indicates that stock market participants accurately identify and assess the effect of the different bank strategy variables on

[30] Our sample period does not span the extreme events of the global financial crisis that started in 2007. See e.g. Shehzad and De Haan (2013), for a study that analyzes the drivers of bank stock performance in the global financial crisis.

[31] The capital measure used in this paper is the Tier 1 risk-based capital ratio. However, as mentioned in Ashcraft (2008), the relevant capital measure for regulators is equity capital plus subordinated debt, as this is the cushion regulators consider before the claims of depositors are affected. Comparison of both capital measures indicates that the correlation is very high. Estimating the frontier set-up with the regulatory capital measure yields similar results. They are available upon request.

[32] Bank size is, to a large extent, the outcome of strategic choices made by banks and is hence highly correlated with the other control variables, and, more importantly, with the measures that capture the various business models we consider. Therefore, we orthogonalize size with respect to all other variables. The natural logarithm of total assets is regressed on all independent variables. The idea is to decompose bank size in an organic growth component and a historical size component, the residual.

semi-volatility and the market-to-book value. Larger banks have a higher market-to-book ratio. More cost efficient banks, with less credit risk (higher asset quality) that are more profitable will have lower risk and higher valuations. A larger regulatory capital ratio makes banks safer but harms their long-term value.

Funding Structure We decompose total deposits in three types: Interest-bearing core deposits, non-interest-bearing deposits and wholesale funding. The first is the share of deposits held by retail depositors, which are protected by the deposit insurance scheme. Wholesale funding providers are generally more sensitive to changes in the credit risk profile of the institutions to which they provide these funds. As such, they are expected to track the institution's financial condition more closely and withdraw money more swiftly when they detect a deterioration in the bank's risk profile. With respect to the funding composition, we find that in our sample (which coincides with the pre-crisis period), there are no differences across deposit types in their effect on SV or MTB.

Asset Mix We find that banks which mainly focus on their core activity (a large loans-to-asset ratio) exhibit lower market-to-book values (but are also less risky). Next to including the loan-to-asset ratio, we classify loans according to borrower types. The loan portfolio composition[33] may have an impact on stock market participants' perceptions of banks' risk exposures. We categorize loans as commercial and industrial (C&I) loans, real-estate loans, consumer loans, agricultural loans and a catch-all share that includes all other loans. We leave the real estate loan share out of the equation to avoid perfect collinearity. Table 1 in the paper shows that banks' loan portfolio composition varies substantially in the sample. The average bank's loan portfolio consists of 63% real estate loans, 19% C&I loans and 12% consumer loans. Banks with a higher proportion of consumer loans face lower semi-volatility. The commercial and industrial loan share has a small positive impact on total risk. Hence, we confirm the evidence by Morgan and Stiroh (2001) who found that bond spreads are increasing in commercial and industrial lending.

Revenue Streams The activities of deposit-taking and lending predominantly generate interest margin. However, some banks also generate a substantial amount of non-interest income (Stiroh (2006)). Therefore,

[33]The FRY9C reports do not allow to distinguish directly between high and low quality loans within each category (e.g.: focus on subprime versus prime loans within real estate loans). Note, however, that such differences should show up in the non-performing loans ratio. Moreover, to the extent that this is a deliberate, time-invariant choice, it will be captured by the bank fixed effects. In unreported regressions, we included charge-off rates by loan type. This does not affect our findings on monitoring and the identification of the risk and valuation signals.

we also include variables capturing the importance of income generated by fiduciary activities and trading-related income. All other activities that generate non-interest income are captured in the other non-interest income share. Previous studies have documented that non-interest income is in general more risky than interest income (e.g. Stiroh (2006b) and Demirguc-Kunt and Huizinga (2010)). Our breakdown of non-interest income in four subcomponents yields additional insights. First, relative to the omitted interest income share, trading revenues and other non-interest income[34] subcomponents lead to higher semi-volatility. Second, banks with a larger fraction of their income generated by service charges on deposit accounts experience lower stock market semi-volatility. However, this coefficient is no longer significant in column 3.

Finally, we include three indicators to measure the potential diversification effects of liquidity risk on the asset and liability side of the balance sheet. Gatev, Schuermann, and Strahan (2009) find scope for **deposit-loan synergies**.[35] Banks exposed to loan-liquidity risk without high levels of transaction deposits have higher risk. Bank risk is expected to rise with unused commitments (reflecting asset-side liquidity risk exposure) and the use of transaction deposits (reflecting liability-side liquidity risk exposure). The synergy effect is measured by the interaction term between the ratio of unused loan commitments and transaction deposits. Two of the three effects are confirmed in our sample. The transaction deposits increase bank risk, but the combination with unused loan commitments provides a statistically and economically significant hedge against liquidity risk and reduces the risk of the bank.

Overall, we can conclude that stock market investors accurately identify the different risks associated with the balance sheet and income statement characteristics and use this in their assessment of the banks' valuation and risk profile. Although this evidence does not yet establish that market discipline can effectively control banking firms, it soundly rejects the hypothesis that investors cannot rationally differentiate among the risks undertaken by the major U.S. banking firms. This is evidence of the first step in market discipline, market monitoring, which is a necessary but not a sufficient condition to support the market influencing hypothesis.

Robustness and remarks As a robustness check, we also include state fixed effects for at least two reasons. First, unobserved heterogeneity at the state level, such as state-specific regulation or the composition

[34] Other non-interest income are predominantly fees and commissions from investment banking and underwriting, (re)insurance underwriting and venture capital revenue.

[35] Quijano (2013)'s results provide an additional motiviation to control for deposit-loan synergies.

of the local economy may affect banks' riskiness as well as their business mix. Second, Mester (1997) has documented that controlling for heterogeneity in stochastic frontier analysis is important to obtain accurate estimates of inefficiency. Rather than estimating the frontier at the state or region level, which would yield imprecise estimates as the number of observations is small for many states, we allow the intercept of the stochastic frontier to be different across states. Significance and magnitude of the coefficients are quite similar in both specificiations. In the few differences, we never obtain conflicting results in terms of sign. It is worth stressing that the (rank)correlation between the inefficiency scores with and without state fixed effects is almost perfect. In sum, including state fixed effects does not alter the results.

In the multiplicative heteroscedastic regression setup (the setup for MTB), we cluster the standard errors at the bank level (which yields the most conservative standard errors). Unfortunately, clustering techniques have not yet been implemented in the standard stochastic frontier models. Moreover, it is even more complicated in our extended approach in which we also model the variance of the inefficiency score. Fortunately, as clustering does not affect the coefficients or inefficiency score/residual, but only the standard errors of the coefficients; our setup to test for the presence and strength of influencing (which is our main contribution) is unaffected by the choice of clustering.

Finally, the signals obtained from estimating a model with and without scale heterogeneity (i.e. modelling the variance as a function of bank characteristics) are very similar. The correlation between the inefficiency scores in column 1 and 3 is 95%, whereas the correlation between the residuals of equation 2 and 4 is even higher 98%. Recall that we defined signals as belonging to the highest decile. 84% of the SV signals based on column 3 would also be classified as signals in column 1. An additional 14% of signals based on column 3, belongs to the 9th decile (rather than the 10th decile) if signals were based on column 1. The correspondence is even higher with respect to market-to-book-signals. 90% of the MTB signals based on column 4 belong to the extreme decile based on column2. An additional 9.6% belongs to the 9th decile of residuals based on column 2.

Table A.1: Semi-Volatility and Market-to-Book: evidence of monitoring

	Semi Volatility SFA	Market-to-Book OLS	Semi Volatility SFA (with scale)	Market-to-Book Cond. Het. reg
Bank Strategy Variables				
Bank Size	0.000172	0.183*	-0.00112	0.231**
	(0.00319)	(0.110)	(0.00313)	(0.0932)
Tier 1 Risk-Based Capital Ratio	-0.0137***	-0.277***	-0.00932***	-0.273***
	(0.00184)	(0.0471)	(0.00184)	(0.0423)
Non-Performing Loans Ratio	0.0139***	-0.0862***	0.00940***	-0.0948***
	(0.00113)	(0.0299)	(0.00120)	(0.0253)
Cost to Income	0.00182	-0.128**	0.00302	-0.148***
	(0.00190)	(0.0592)	(0.00191)	(0.0520)
Return on Equity	-0.0120***	0.0868***	-0.00709***	0.124***
	(0.00111)	(0.0221)	(0.00125)	(0.0227)
Liquid Assets	0.00569***	0.00473	0.00390**	0.0204
	(0.00165)	(0.0362)	(0.00161)	(0.0304)
Funding Structure				
Interest-Bearing Core Deposits Share	-0.000799	-0.0407	-0.00172	-0.0202
	(0.00361)	(0.0748)	(0.00358)	(0.0646)
Wholesale Funding Share	-0.00208	-0.0819	-0.00209	-0.0655
	(0.00366)	(0.0780)	(0.00358)	(0.0662)
Deposits to Total Assets	-0.00350	-0.0666	-0.00167	-0.126**
	(0.00229)	(0.0668)	(0.00224)	(0.0574)
Asset Mix				
Commercial and Industrial Loan Share	0.0117***	-0.0308	0.0136***	0.0111
	(0.00227)	(0.0512)	(0.00225)	(0.0427)
Agricultural Loan Share	-0.00105	-0.0404	0.000762	-0.0483
	(0.00213)	(0.0382)	(0.00205)	(0.0367)
Consumer Loan Share	-0.0116***	0.00345	-0.0107***	0.0363
	(0.00229)	(0.0644)	(0.00224)	(0.0526)
Other Loan Share	0.00480**	0.139**	0.00578***	0.118*
	(0.00227)	(0.0651)	(0.00223)	(0.0669)
Loans to Total Assets	-0.00714***	-0.120***	-0.00588***	-0.120***
	(0.00186)	(0.0455)	(0.00183)	(0.0387)
Revenue Streams				
Fiduciary Activities Income Share	0.00703**	0.199	0.00826***	0.286**
	(0.00274)	(0.161)	(0.00272)	(0.122)
Service Charges on Deposit Accounts Share	-0.00413**	0.0423	-0.00187	0.0306
	(0.00210)	(0.0590)	(0.00206)	(0.0476)
Trading Revenue Share	0.00491***	0.0707**	0.00425***	0.0803**
	(0.00157)	(0.0350)	(0.00150)	(0.0316)
Other Non-Interest Income Share	0.00841***	0.167***	0.00748***	0.170***
	(0.00185)	(0.0561)	(0.00190)	(0.0505)
Deposit-Loan Synergies				
Deposit Loan Synergies	-0.00646**	-0.108*	-0.00650**	-0.0925
	(0.00306)	(0.0617)	(0.00299)	(0.0599)
Unused Loan Commitments Share	-0.000626	0.112	0.00118	0.0959
	(0.00294)	(0.0710)	(0.00288)	(0.0645)
Transaction Deposits Share	0.00438*	0.0300	0.00530**	0.0438
	(0.00263)	(0.0553)	(0.00255)	(0.0472)
Observations	17264	17216	17264	17216
Bank Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This table presents estimation results for equation (1) in the paper. Columns 1 and 2 contain the results of the stochastic frontier model (semi-volatility) and the conditional heteroscedastic regression model (market-to-book value of equity). Column 3 contains the results of the stochastic frontier model (semi-volatility) where the variance of the inefficiency term is a function of bank-specific characteristics (hence, we allow for scale heterogeneity). Column 4 contains the results of the conditional heteroscedastic regression model, in which the volatility of the error terms is a function of bank characteristics. We estimate a 'cost' function for total risk. That is, the inefficiency score measures excess risk above the frontier, which is determined by the banks with minimum risk given a set of bank characteristics. In particular, stochastic frontier analysis allows decomposing the error term in random noise and a measure of risk inefficiency. As firms (banks) can be both over- or undervalued with respect to their fundamentals, we employ a standard OLS regression model (with both positive and negative residuals) rather than a stochastic frontier model which only allows for one-sided deviations from the frontier. The variables are measured over the period 1991-2007 at a quarterly basis. Bank balance sheets are observed and measured as stock values at a quarterly basis. Data from the income statement is reported on a cumulative basis over the accounting year and are therefore first transformed to quarterly increments. The independent variables are lagged one quarter. The sample includes all US Bank Holding Companies that have publicly traded equity for at least four consecutive quarters. Furthermore, we exclude banks of which the stock has zero trading volume for more than 20 percent of the observations. The total sample consists of 17.264 observations on 899 bank holding companies. Time and bank fixed effects are included in each column (but not reported). In the second column, the standard errors are robust and clustered at the bank level.